Gender and Racial Wage Gap on Delivery Platforms

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Abstract

This study analyzes wage differences both by gender and by race in a delivery app. We examined 133,856 workers observed both in the delivery platform databases and in the traditional formal labor market. It was observed that in the traditional formal jobs, there is a significant gender and racial wage gap, with women and blacks with lower earnings than men and white workers with equivalent observable characteristics. On the delivery platform, lower average earnings were also observed for women. However, the gap was smaller, and it can be explained by variables associated with productivity and efficiency that differ between male and female drivers, such as the use of motorcycles and turnover levels. However, the same gap reduction could not be verified for black workers.

Keywords: Gig Economy, Wage Inequality, Gender, Race, Delivery App
JEL: J71, J31

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1. Introduction

Holding high levels of socioeconomic inequality, Brazil has a labor market with considerable discrimination, in which the disparities both on gender and race are more significant. At the wage inequality ranking of the America continent, Brazil is the second-to-last, with Chile being last (World Economic Forum, 2020). Despite all progress and achievements by women and black people on the labor market, gender and racial wage gap persists. In Brazil, women receive on average 77,7% of men's earnings (IBGE, 2021). Beyond pay disparity between man and woman, black or mixed-race people received 57,5% the income of white workers (IBGE, 2019). In part, the gender inequality could be explained by factors such as inflexibility of work hours

(Goldin, 2014; Mas and Pallais, 2017), maternity's penalty (Kleven et al., 2019) and factors not related with productive characteristics.

The gig economy is a global phenomenon that has altered the labour market dynamics on a growing number of sectors. This new kind of work relation is characterized by internet platforms that connect with autonomous service providers with their consumers and offer flexible job options. With this type of configuration, platforms act as mediators between parts, reducing entry barriers and autonomous services cost. As such, its been discussed on labour economics literature that this new growing phenomenon could reduce wage gaps.

On this context, the Brazilian delivery applications market has been highlighted by its notable growth. On 2019, the sector had an increase of 20% compared to the year before, resulting on a R$15 billion revenue. Personal attributes such as gender or race, in theory, are not considered for provision of services on those online platforms. Therefore, a neutral payment platform should not have any kind of discrimination or segregation in regards to the providers compensation. Although different studies have identified that pay differences keep being observed on the theoretical neutral platforms of the gig economy (Cook, 2021; Adams-Prassl, 2020; Liang, 2018). However, this new literature still has important questions unanswered, such as wage inequality related to race and the existence of pay inequality on emerging economies as Brazil, for instance. This present work seeks to fill theses gaps exploring if the Brazilian delivery applications market has persistent different earnings between woman and man, and also among black and white.

An unique aspect of the present work is the use of data from one of the largest delivery applications on Latin America. This paper will be one of the first to look at a gig economy Brazilian firm and to explore both gender and racial wage difference. Another important contribution is the comparison of pay differentials of the same group of workers on these kind of platforms and on the formal labour market. Thus, this study analyses 133.856 workers are observed simultaneously on the delivery platform data and on formal employment Brazilian database, the Annual List of Social Information (Relação Anual de Informações Sociais- RAIS). Combining these datasets and with sample selection, it was possible to monitor earnings of a cohort of workers before and after entering the delivery application market, allowing comparisons of pay on both cases. This wage was evaluated by a Mincer Earnings Regression, that seeks to estimate the relation between workers gains with observed characteristics, such as gender, race, experience, education, age and so on. The regression coefficients are estimated for gains both on the delivery platform and the formal market, allowing comparisons of the earnings differentials by gender and race for the same group of individuals.

The present study's results reveal that there is a significant wage differential on both gender and race, with women and black having a lower average pay compared to men and white workers with equivalent observable characteristics on the formal market. While on the delivery applications market, the employees earnings also has significant differences regarding gender. However, this wage gap on the delivery platforms is smaller and can be explained by variables associated with productivity and efficiency that differ men and women, such as the use of motorcycles and turnover. With the inclusion of such variables as controls, the earnings differential inverts, and it is observed that women receive 2.08% more than man with the same observable characteristics, validating the payment platform neutrality theory. Nonetheless, this same wage gap reduction is not verified in regards to racial differentials.

2. Literature Review

2.1. Gender and Race Pay Gap Theoretical Evidence

Economic theory disposes different interpretations over the wage discrepancy among genders and races. Stated by Schultz (1961) and popularized by Becker (1962), Human Capital Theory arise from the need to explain the wage determination process, given the pay difference on the labour market assumption. The theory exposes that, as long as individuals educational and ability levels rises, the wages increase proportionally because of productivity enhancement, that determines salary. Thus, accumulated human capital stock by a person would be resulted from investment on human capital and therefore would raise pay. However, this theory does not incorporate other factors that might accentuate wage inequality on both gender and race, but not associated with differences on human capital investment. Inclusion of such variables on salary models occurred with Segmentation Theory from Doeringer and Piore (1970) and Statistical Discrimination Theory by Arrow (1971) and Phelps (1972).

Segmentation Theory describes that the pay discrepancy can not be explained solely by human capital investment, since even though being a significant discretion, its only a selection criteria. The theory discusses with respect to existing a fragmented labour market in two segments, where workers with same productivity have distinct salary because its the individual features of employees that determines on which segment they are allocated. The first sector is related to people with privileged working conditions, being defined by high qualification level workstations, earnings and productivity. The second segment, qualified as a peripheral, is composed by vulnerable situation jobs, high turnover and low wages and productivity.

Already on Statistical Discrimination Theory, differentiation arise from a imperfect information problem encountered by economic agents, and not by a market segmentation problem. This theory states that a decision maker, even though not being a discriminator, and for not having perfect information over individual's productivity, bases on the person's group performance history at the time of the hiring decision. In other words, the agent decides basing on a group average feature that such individual participates instead of focusing on the specific labourer characteristics.

Beyond the cited theories, other interpretations are present on the literature supporting the wage discrimination subject. According to Goldin (2014), jobs that offer flexible hours, as on the pharmaceutical industry, are closer to achieve equal pay between men and women. Cubas and Juhn (2019), estimate more than half of gender salary difference comes from women's inflexibility. Mas and Pallais (2017) realise, on an experimental environment, that women are more willing to renounce almost 40% of wages to avoid irregular hours. Reyes (2007) analysed the obstetrician and gynaecologists markets providing additional evidences that high-skilled women with good labour market perspectives chooses positions with less working hours and more steady schedules. On an environment that demands plenty working time, these choices lead to significant difference of earnings across genders.

As for racial discrimination, the salary disparity between black and white has been widely studied in the United States. The mismatch of black and white men converged markedly since the sixties, largely due to higher levels of education and educational return to pay of black workers. According to Patten (2016), on average, white labourers earn larger hourly pay than black employees, with white men making around 30% more than black coworkers, while white women were earning around 25% more than their counterpart. Although black men tend to be payed less than white men, black women's average pay presents smaller differences compared to white women (Altonji and Blank, 1999; Couch and Daly, 2002; Fryer, 2011). Charles and Guryan (2008) stated that around a quarter of the unconditional racial disparity salary would be on account of prejudice, while the rest could be due to non-observable characteristics or other forms of discrimination.

On the Brazilian market, racial wage inequality is also an extensively studied subject. Lovell (1994) pointed out, with data from 1960 and 1980 Census that, in Brazil, even isolating and controlling with explanatory variables, white still earned more than black individuals. With the goal to verify the earning difference determinants among white men with others group of workers, Soares (2000) utilized PNAD data from 1987 and 1998 to conclude that black men received around 5% to 20% less than white men, where the major difference was on the higher compensated groups of the population, in other words, black men with higher pay tend to receive less that white men on the same category. And even overtime, Zucchi and Hoffmann (2004) showed with PNAD 2001 data that black workers gained income, on average, 43.8% lower than white employees on the Brazilian labour market. And that 21.7% to 26.8% of this differential corresponded to portion of factors not related to productivity, that is, according to the labourers color. Guimarães (2006), investigated racial wage gap causes utilizing micro data from PNAD 2002. Among the results found, it can be observed that color discrimination is present in the Brazilian society and that black individuals salary is, on average, 17% less than white workers. A more recent study from Gerard et al. (2021) highlights companies policies effect on racial differences in Brazil, in which stated that non-white are less likely to being hired by high pay businesses.

2.2. Empirical Evidence of Gender and Racial Wage Difference on the Gig Economy

The debate over pay disparity between men and women concentrate most of the times on the employers discrimination, being it explicit or not, and the consequent implications for men and women salary in the workplace. Recently, however, new debate has surged that analyses directly the gender wage mismatch relation with the gig economy, in which the workers sex is unknown to the employer. A study published by the platform Hyperwallet (2017), reports that 86% of women's workers on this new economy believe the sector offers opportunity of equal pay. Such question was analysed on works by Adams-Prassl and Berg (2017); Zoe B. Cullen and Pakzad-Hurson (2018); Liang (2018); Adams-Prassl (2020) and Cook (2021).

A pioneer study over this topic is a discussion Adams-Prassl and Berg (2017), that utilizes data from an online platform of collective work in which labourers sex is unknown to the employer to evaluate if there is gender salary disparity. In this scenario, it was stated that women earn, on average, 82%

less than men. However, a deeper analysis revealed that income differences does not take place during the platforms use itself, but rather by workers individual characteristics, such as collective jobs experience and educational level.

The work from Zoe B. Cullen and Pakzad-Hurson (2018) highlights that patterns on pay differentials, on temporary jobs applications, are similar to standards on the economy as a whole. Such result suggest that platforms can be limited to its capacity on handling inequality. Along similar lines, Liang (2018) study the wage difference on the gig economy through working platform "Freelancer.com". The results reveal that women earn around 81.4% men's hourly wages, and that women tend to have higher disposition paying to avoid the "work flexibility penalty".

Recently, Adams-Prassl (2020) examined gender discrepancy on working standards and hourly salary at Amazon Mechanical Turk (MTurk), a fairly popular online labour market. Using information of 2 million tasks, it did not encounter a gender difference on assignment selection nor platform experience. Even though, it stated that women receive 20% less per hour compared to men. A follow-up research showed that pay disparity is concentrated on women with small children, that also report that domestic responsibilities affect their planning capacity to conclude the online work. At last, a most recent study from Cook (2021) also portray a gender wage difference of approximately 7% on share rides on Uber in the United States. The study indicates 36% of this discrepancy is explained by the fact that men accumulate more experience than women and 28% of gender disparity on where and when to drive, and the remainder could be explained by preferences related to conduction speed.

Despite gender analysis results, there is no recent evidence that address racial wage inequality question on the gig economy. Novel research concentrate on racial discrimination analysis of consumers of such platforms, in other words, service contractors, but not providers. Precursor work on this literature is Doleac and Stein (2013) paper revealed that iPod sales online ads with hands of persons of color's skin received less offers than advertisement with pictures of hands with white skin. Ayres et al. (2015) observed black salesman at eBay earn less than white sellers. Edelman et al. (2017) observed at Airbnb that guests with African-American names were 16% less likely being accepted by hosts than visitors with identical characteristics, except clearly white-related names. At last, Y. Ge and Zoepf (2020) ascertain that, on share travel platforms as Uber and Lyft, black passengers were submitted with longer waits and higher cancellation rates than white riders. Thus, this present work aims to add to the literature evidences that address wage inequality related to gender and race of individuals at the gig economy, by using data from one of the largest delivery platforms of Latin America.

3. Context and Data

3.1. Delivery App Market

Product and food delivery at home is a long existence reality. Thanks to increasing smartphone and internet connection insertion, daily delivery practice spread on most countries. According to data by research TIC Domicílios (2021)[1] promoted by the Brazilian Internet Steering Committee (CGI.br), it is estimated that, on 2020, 81% of the Brazilian population with ten or more years have access to internet and almost all users (99%) utilizes smartphone as the main device to access online network.

In Brazil, food delivery by application sector exists since 2007 and has grown gradually. Consumers are adopting online meal courier service for its convenience, practicality and agility, while providers of food services see a potential for increasing revenue, lowering workforce expenditure and reducing logistical costs.

Composed by companies such as Loggi, IFood, Rappi and 99, the delivery app market invoiced R$ 15 billion in 2019, a 20% growth compared to 2018, according with research made by a representative of the food sector, the Associação Brasileira de Bares e Restaurantes (Abrasel)[2]. Currently, beyond meal delivery, platforms offer other services, as courier service of supermarket, pharmacy, pet shop. and beauty products.

Recently, with COVID-19 pandemic and social isolation, the delivery application sector gained larger prominence in the economy and had surprising expansion. Survey made by Statista[3] - a firm specialized on market and consumer data - shows Brazil as a highlight on the courier service in Latin America in 2020. The country was in charge of almost half delivery numbers, 48.77%, followed by Mexico and Argentina with 27.07% and 11.85%, respec-

[1] `https://cetic.br/pt/pesquisa/domicilios/indicadores/`

[2] `https://abrasel.com.br/noticias/noticias/do-celular-a-mesa-como-os-apps-de-delivery-transfor`

[3] `https://www.statista.com/topics/6732/online-food-delivery-in-latin-america/#dossierContents__outerWrapper`

tively. Data from the sector shows a leap of 155% on users accompanied by orders expansion, achieving expressive 975% increase.

Following the rise of this market, the number of workforce also extended. In 2016, 30 thousand people worked on goods application platforms. In the second quarter of 2021, this number got to 278 thousand, an increase of 979.8% in the past 5 years, according with a study from the Institute for Applied Economic Research (IPEA)[4].

3.2. Delivery App Platform

The courier service application analyzed is one of the largest gig economy firms in Latin America.

Deliverer's salary is defined by the own platform in a proprietary system of payment by completed order. This value is a function of distance traveled and a minimum by goods supplied. However, pursuant with the number of requests, city profile, hour, weekday and means of delivery (car, motorcycle, scooter or bicycle), final value can have variations. Beyond these factors, the deliverer also receives additional fee for each kilometer of the total distance from restaurant's distance. The application allows tip. However, those were not registered at the database utilized in this present work. Therefore, in this study, tips were not considered on the final deliverer's remuneration. According with this formula, service payment does not depend on gender or race of the service provider. Furthermore, similarly to other competitors of the gig economy, there is no gains negotiations with the delivery platform. It is worth to emphasize that the courier service application does not offer to its service providers benefits available at formal jobs, such as severance pay, maternity leave and unemployment insurance.

3.3. Data

Work wage differential investigation arise from workforce data analyses that provide delivery services in Brazil using the courier service platform between 2019 and 2020, in conjunction with information of the same employees when they occupied traditional formal jobs between 2015 and 2018. Information on formal employment are available at RAIS.

RAIS is a dataset made available by the labor ministry, and its purpose is to compile cadastral information of all employed with work record booklet

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[4] `https://www.ipea.gov.br/portal/images/stories/PDFs/conjuntura/211216_nota_5_gig_economy_brasil.pdf`

and of every company registered with a Brazilian tax identification number, the Cadastro Nacional de Pessoa Jurídica (CNPJ). Government uses this information as a way for fiscal controlling, such as income tax collection or other firm related taxes. Every business with CNPJ are obligated to inform its facility locations and information about its employees.

Such database had, in 2018, approximately 66.2 million records of people with work record booklet. From this data, filter were applied and restrictions made to remove workers fired during the year. To that end, only workers who had an employment relationship in December of each year were kept. To remove bad input from the dataset, it were selected only employees: i) with income greater than zero; ii) age between 16 and 80 years old; iii) weekly work time higher than 1; iv) that had a record at a government occupation identification register, the Classificação Brasileira de Ocupações (CBO); v) without duplicate information on the same worker, retaining only the data of the employee with the higher wage in such cases.

At the delivery platform database, it was considered only active working people at the application at some moment between 2019 and 2020, finding a total of 671.299 individuals. However, a filter was applied for deliverers with 20 or more orders completed in this period, and the other delivery workers were discarded. With such restriction, 330.963 individuals remained on the data, representing around 40.6% of the initial dataset. Then, information from laborers observed in the formal market in 2018 was merged using the RAIS database, and only workers present in both databases were selected. This combination was made using a employee identifier, an encrypted Individual Taxpayer Registration (CPF), which matched individuals present both in the formal market in 2018 as well as in the delivery platform data between 2019 and 2020 in all national territory. With such union, 133.856 workers were observed on both databases and made at least 20 deliveries between 2019 and 2020.

For labourers observed on RAIS, gross monthly wage per hour was calculated based on individuals earnings provided by RAIS. First, by finding the number of hours hired, by month, of each worker. Then, dividing the salary by the number of hours hired, resulting on gross payment by hours worked. For platform deliverers, it was calculated the total earnings directly by the number of hours worked by each individual, with the time spent with labour on the platform straightly available by the platform's data. It is important to highlight that worker's remuneration on the courier service application does not consider benefits or obligated official discounts.

Thus, with observed labourers and the respective gross earnings by hours worked, observations from each base below 1 percentile and above 99 percentile hourly wages were eliminated. This process was made to exclude imputation errors and existing outliers on the databases.

3.4. Descriptive Analysis

Table 1 presets data of all workers observed on RAIS 2018 and on the delivery platform 2019 and 2020 dataset. It is worth noting that, of all individuals observed, 94.9% are men, while only 5.1% are women, as illustrated at column (1). In regards to race, among black deliverers, 95.1% are men and 4.9% are women, according to column (5).

When examining workers mean age, black labourers have 27.7 years, while white workers are above 28 years. With respect to educational level, 81.2% of deliverers have completed secondary school. This statistic goes down to 79.9% when considering only women, at column (3). On the other hand, 11.7% of women have completed college education, in comparison to 6.4% to the total database mean.

Descriptive Analysis from Table 1 also suggest that on the formal labor market, there is a gender and racial mean wage differential at the sample. In 2018, when workers were on the traditional sector, average earnings by hours worked was R$9.93 for men. As for women such mean was R$9.29 per hour, around R$0.64 less. For the sample analysed, these data supports research results from the United Nations (UN) (2019)[5] that revealed that, in Brazil, women have more years of study than men, but receive 41.5% less. In regards to race, white deliverers have the highest income, with R$10.17, around R$0.61 higher than black, endorsing the initial statement that white receive more than black. When comparing formal market and delivery platform salaries, it is worth noting persistent income differential, but are mitigated. Deliverers hourly wage is R$10.02, with women receiving R$9.90, approximately R$0.12 less than men. White courier service providers maintain higher earnings, with R$10.13.

Before working at the delivery platform, 86.8% of identified individuals were active in the service sector, while 12.9% worked at manufacturing. In regards to hours contracted by month, women have 4 hours less than men. As for race, all have, practically, the same hours employed.

[5] `https://www.br.undp.org/content/brazil/pt/home/library/relatorio-do-desenvolvimento-humano-2019.html`

When highlighting transportation means utilized by individuals to practice their professional activity on the courier service platform, the analysis was categorized into two groups: The first group is composed by the motorcycle modal, that includes workers that have at least 1 delivery at the platform using a motorbike as means of transportation. The other group refers to workforce that made its deliveries at the platform utilizing other modes. It is noticed that 85.4% of the sample uses motorcycle as means of transportation to complete orders through the delivery platform. This data is confirmed when it is observed that, from all courier services made, 91.1% are made by motorbike. However, even though the majority of deliveries are made by motorcycles, women's percentage that use this modal is the lowest among all categories. Only 72.4% of women completed their orders using motorbikes.

Table 1: Sample Descriptive Statistics

	Total	Gender		Race	
		Men	Women	White	Black
	(1)	(2)	(3)	(4)	(5)
Total Workforce[1]	133.856	126.963	6.893	58.688	56.878
Gender					
Men	94.9%	-	-	94.6%	95.1%
Women	5.1%	-	-	5.4%	4.9%
Race[2]					
White	43.8%	43.7%	46.2%	-	-
Black	42.5%	42.6%	40.8%	-	-
Average Age	28,0	28,0	28,1	28,3	27,7
Education[3]					
Early Childhood	1,3%	1,4%	1,0%	1,2%	1,5%
Elementary	11,1%	11,3%	7,4%	10,7%	11,0%
High School	81,2%	81,3%	79,9%	81,1%	82,0%
College	6,4%	6,1%	11,7%	7,0%	5,4%
Employment 2018[4]					
Hourly Wage[5]	R$ 9,90	R$ 9,93	R$ 9,29	R$ 10,17	R$ 9,56
Contracted Hours	181,9	182,1	178,0	182,7	181,6
Services	86,8%	86,5%	91,6%	85,0%	87,9%
Manufacture	12,9%	13,1%	8,3%	14,6%	11,8%
Delivery Platform 2019/2020					
Transportation Modal[6]					
Motorcycle	85,5%	82,4%	3,1%	38,4%	35,3%
Others	14,5%	12,4%	2,1%	5,4%	7,2%
Average Deliveries	486,4	495,8	313,5	493,6	481,9
Percentage of Motorcycle Deliveries	91,1%	91,8%	72,3%	92,5%	89,3%
Hourly Compensation[7]	R$ 10,02	R$ 10,03	R$ 9,90	R$ 10,13	R$ 9,91

[1] Total number of individuals working on the delivery platform found in the 2018 RAIS database.
[2] The racial/skin color categories are the same as those used by the Annual Social Information Report (RAIS).
[3] The education level considered is the completed education level.
[4] Represents the employment data from RAIS.
[5] Hourly Wage refers to the gross payment per contracted hour of workers observed in RAIS.
[6] The Modal category refers to the means of transport used by individuals. "Motorcycle" refers to workers who made at least one delivery on the platform using a motorcycle. "Others" refers to workers who made deliveries on the platform using other means such as cars, bicycles, scooters, among others.
[7] Hourly Compensation refers to the gross hourly compensation of platform workers.

4. Estimation strategy

In order to analyze these individuals salary differential, an option was made for a simple linear regression through a Mincer equation for wage determination. This modeling aims to estimate the relation of workers earnings and observable characteristics such as gender, race, experience, education, age an so on. This regression coefficients are estimated for both gains on the delivery platform and on the formal traditional market when these individuals were there, allowing for comparisons on differentials of income on gender and race in both situations, controlling for observable characteristics.

Therefore, two wage regressions were estimated: one where the dependent variable was hourly pay on the formal market, the other where such variable was earnings per hour when the same group of individuals were deliverers on the platform. Control variables included on both regressions came from individual observable characteristics on RAIS, that is, sex, age, race, education, disability, sector, occupation and city of work. Formally, estimations can be described by the following equations:

$$y_{i,2018} = \beta_{FM} X_{i,2018} + \epsilon_{i,2018}$$
$$y_{i,2019/2020} = \beta_{DP} X_{i,2018} + \epsilon_{i,2019/2020}$$

The first equation (1) estimates wage regression for the formal market and its dependent variable is $y_{i,2018}$, that measures logarithmic earnings per hour of workers on the formal market in 2018, $\beta_F M$ is a vector with coefficients of interest from the formal market, $X_{i,2018}$ is a vector with observed individual features in 2018 and $\epsilon_{i,2018}$ is the idiosyncratic error term. As for equation (2), the dependent variable is $y_{i,2019/2020}$, which represent the logarithmic income per hour from deliverers on the platform between 2019 and 2020, and $\beta_D P$ is a vector with coefficients of interest that measure the relation of observable variables and workers hourly wages.

5. Results

Table 2 shows regressions (1) and (2) results, each one estimated on two different models in regards to the fixed effects inclusion. Columns (1) and (3) have no sector and occupation controls observed in 2018. As for columns (2) and (4), there is the inclusion of these controls. Considering only the first situation, where no fixed effects in 2018 are considered, it is observed that women of the sample gain, by hour worked, 8.27% less than men in the formal market. As for the delivery platform, such pay differential was 2.08%. From the racial perspective, black labourers earn 0.89% less than white in the formal market, with this difference still existent in the delivery platform, but decreased to 0.44% less for black workers compared to white.

When examining deliverers age co variable, it is noticeable that, on the formal market, there is a significant wage growth as age increases. However, such rise is not observed on the delivery platform. In regards to education, it has been found that, in the formal market, there is significant pay growth with increased education. This positive relation supports Human Capital Theory, which suggests that as an individual's education grows, their productivity and income increase proportionally. Yet, on the delivery platform, the opposite is observed, where a wage decrease comes with educational growth. The real reason for this scenario is unknown, but a possible explanation is that deliverers with college degree see the courier service application as a secondary source of revenue, in other words, work as deliverers only as a mean to complement the main source of income.

At the second set of estimations, where there is occupational and sector fixed effects in 2018, it was verified that, in the formal market, women from the sample earned, by worked hours, 5.83% less than men. On the delivery platform, women's salary differential was 1.43%. From the racial perspective, both in the formal market and the courier service application, black workers received less than white labourers. In regards to age, in the formal market, wage growth with age has remained. Now on the delivery platform, this same gain was not observed. However, it is noted an increase on income, although not significant, for workers with 60 years or older. An explanation for this kind of effect is unknown, but, according to Cook et al. (2019), while traditional jobs gain grows by age, benefits from gig economy workers, as Uber drivers, are essentially stable from 20 to 40 years old, and have a tendency of constantly lowering from this age range onwards. However, according to the study by Chen et al. (2019), a possible justification for wage's increase for workers above 60 years old is the possibility of the gig economy being perceived by older individuals as a way to continue in the labour market without foregoing their retirement benefits, allowing a choice of working hours and intensity that meet their needs and capabilities. Finally, in regards to workers education, there is still a significant pay rise followed by educational growth in the formal market, while the same is not observed at the delivery platform.

Table 2: Wage Determinants in the Formal Market and in the Delivery Platform

	Wage Differential			
	Formal Market (RAIS)		Delivery Platform	
Variable	(1)	(2)	(3)	(4)
Women	-0.0827***	-0.0583***	-0.0208**	-0.0143*
	(0.0050)	(0.0038)	(0.0068)	(0.0058)
Physical Disability	0.0013	0.0146	-0.0016	0.0005
	(0.0127)	(0.0120)	(0.0107)	(0.0106)
Race[1]				
Black	-0.0089**	-0.0027	-0.0044*	-0.0037*
	(0.0028)	(0.0020)	(0.0018)	(0.0016)
Age[2]				
16-18	-0.2200***	-0.1800***	-0.0203	-0.0173
	(0,0080)	(0,0061)	(0,0109)	(0,0092)
18-20	-0,1097***	-0,0833***	-0,0093*	-0,0064*
	(0,0036)	(0,0030)	(0,0040)	(0,0032)
25-30	0.1133***	0.0807***	0.0028	0.0005
	(0.0053)	(0.0042)	(0.0034)	(0.0024)
30-35	0.1844***	0.1282***	0.0088**	0.0045
	(0.0071)	(0.0062)	(0.0027)	(0.0024)
35-40	0.2134***	0.1497***	0.000286	-0.0051
	(0.0107)	(0.0067)	(0.0052)	(0.0038)
40-50	0.2384***	0.1671***	0.0016	-0.0044
	(0.0118)	(0.0070)	(0.0049)	(0.0037)
50-60	0.2621***	0.1948***	-0.0170	-0.0200*
	(0.0184)	(0.0141)	(0.0090)	(0.0087)
60-120	0.2272***	0.1296**	0.0553	0.0529
	(0.0469)	(0.0438)	(0.0449)	(0.0510)
Education[3]				
Complete Early Childhood	-0.0157	-0.0053	0.0156**	0.0143*
	(0.0154)	(0.0112)	(0.0057)	(0.0057)
Complete Elementary	-0.0118	-0.0215**	0.0032	0.0036
	(0.0077)	(0.0072)	(0.0036)	(0.0032)
Complete College	0.2104***	0.1154***	-0.0170***	-0.0129***
	(0.0095)	(0.0058)	(0.0025)	(0.0033)
Fixed Effects				
Municipality	yes	yes	yes	yes
Sector (2018)	no	yes	no	yes
Occupation (2018)	no	yes	no	yes
Observations	133.856	133.856	133.856	133.856
R^2	0,217	0,387	0,116	0,128

Reference groups: 1 White men; 2 Age between 21-24 years old; 3 Complete High School; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

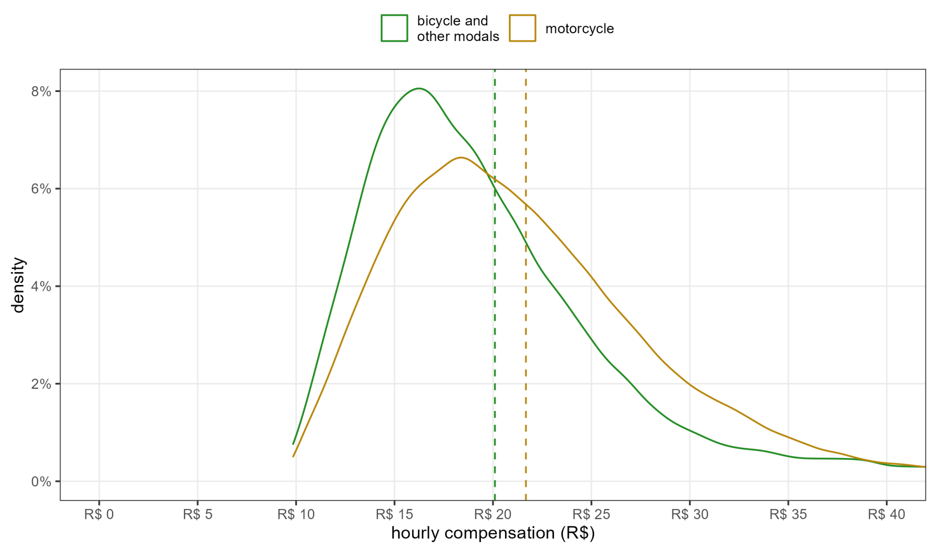
5.1. Investigating Residual Differentials

Given that, in theory, the platform is designed through a "neutral" payment system, in other words, it removes discrimination and segregation situations, this subsection's goal is to investigate the reason for a residual salary differential, as stated beforehand at Table 2.

A search for possible explanations for this remainder differential with variables potentially associated with uneven pay between the analysed groups was made. According to the strategy by Cook (2021), some variables that might be correlated both with individuals earnings and gender or race were selected. The variables chosen for the analysis were use of motorcycles, hour of the delivery and number of courier services made by each worker.

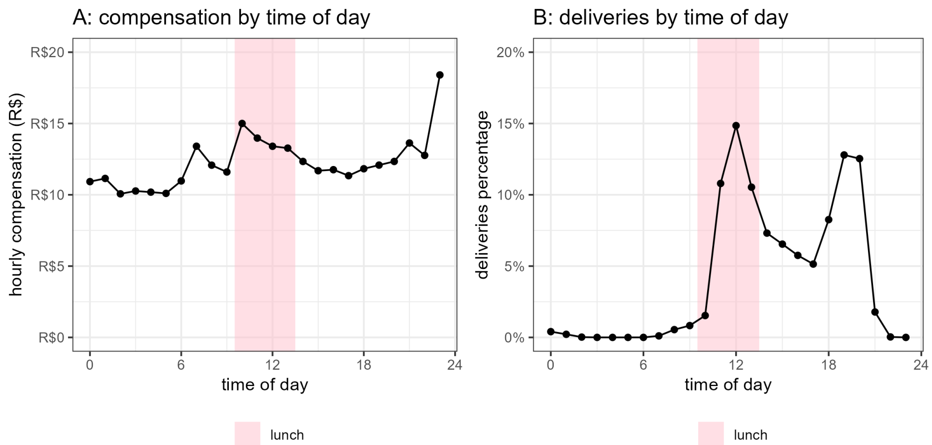
At Figure 1 it is observed that average earnings of motorcycle deliveries are higher than other means of transportation. Therefore, "Delivery by Motorbike" was selected as a potential explanation for the residual pay differential.

Figure 1: Hourly Compensation Distribuion by Mode of Transportation



As for Figure 2, it can be verified that the percentage of deliveries made from 10am to 1pm, considered as lunchtime, is superior than other courier services slots. Not only that, but also earnings on this time range are larger when compared to other time frames. Thus, the variable "Deliveries-Lunch" was prioritize as a possible justification for the residual differential.

Figure 2: Hourly Compensation Differentials by Period - Delivery Platform 2019/2020



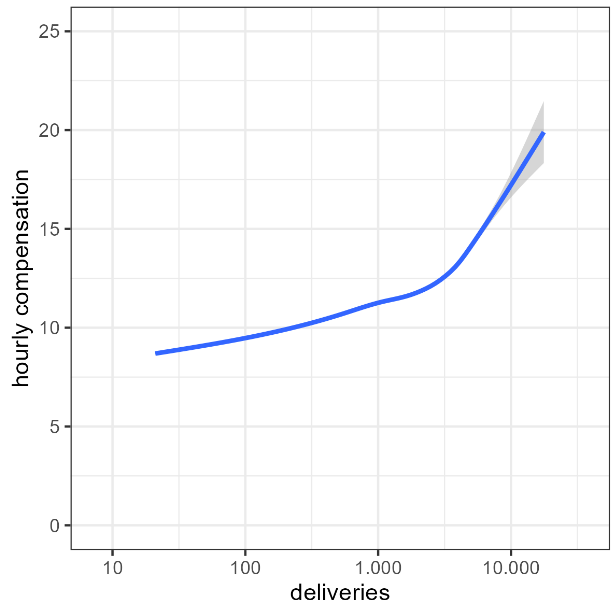
Beyond these possible explanations results suggested by the literature, workers experience can be considered as a explanatory variable of the earnings differential both on gender and race. According to Altonji and Blank (1999), gender income disparity usually increases with labourers years of experience.

Figure 3 highlights the existence of a positive relationship between hourly wage and total deliveries by each courier. Thus, the variable "Deliveries Mean" was selected as a proxy for workers experience on the platform.

At Table 3 it can be seen that exists a difference on the transport modal usage, where men do more deliveries by motorbike than women. Despite "Time of Delivery" being a possible explanation variable, there is not much of a gap on the percentage between groups. Also, there is a difference on average of deliveries made by men and women, where men completed, on average, 495.8 orders, while women from the sample made only 313.5 orders, on average.

Beginning with "Delivery by Motorbike" (column 1), 85.5% of male deliverers made it with motorcycle, while only 59.4% of the women utilized this transport modal. By the racial perspective, use of motorbikes differences are not that intense, however, white make 87.6% of their deliveries by motorcycles, while black people make 83.1%. The age group that uses the most this transport modal is between 35 to 40 years old, with 90.3% of individuals in this age range perform their work activities using a motorcycle. Examining by education, it can be noted that motorbike users have higher education, with 86.3% of deliverers with college degree.

Figure 3: Average Hourly Compensation by Driver's Experience - Delivery Platform 2019/2020



Transitioning to the Lunch Deliveries variable (column 2), women make 37.1% of their deliveries during this higher-paying time, while men make 35% of their deliveries in this same period. By the racial perspective, there is no substantial difference between white and black people. The age range with most deliveries on lunch time is 60 years or more, with 40.4% of completed orders in this slot. On other age ranges, only about 35% of the deliveries are made in this period of the day. According to Chen et al. (2019), a possible explanation is that older individuals choice of working hours and labour intensity possibilities that meet their needs and capabilities. In regards to education, people with complete early childhood education have most orders completed at lunchtime, with 35.8%.

Evaluating the deliveries mean variable (column 3), it can be observed that men did, on average, more courier services than women. Men realized, averagely, 495.8 deliveries, while women had only 313.5. In the context of race, there is a small difference on the mean between white and black, although white made more deliveries. The age range with the most courier services made is from 40 to 50 years. Such information go against wage regression results, where it shows that, on the delivery platform, individual pay lowers as age increases. When analyzing education, individuals that made most deliveries have complete early childhood education, followed by elementary education, with 541.3 and 504.2 deliveries, respectively. College education group has the lowest level of deliveries, averaging 412.7. According to what was presented before, a likely explanation for this circumstance is that workers with this higher education level see the delivery platform as a secondary source of income, only complementing the primary one, while all other educational groups work on the platform to obtain the main source of monthly pay.

Table 3: Descriptive Statistics of Explanatory Variables

	Motorcycle Deliveries Percentage (1)	Lunchtime Deliveries Percentage (2)	Average Deliveries (3)
Total Workforce[1]	85,5%	35,1%	486,4
Gender			
Men	86,9%	35,0%	495,8
Women	59,4%	37,1%	313,5
Race[2]			
White	87,6%	35,1%	493,6
Black	83,1%	35,1%	481,9
Age[3]			
16-18	68,6%	35,2%	337,1
18-20	81,0%	35,1%	387,4
20-25	84,0%	34,9%	444,1
25-30	87,2%	34,8%	478,5
30-35	89,5%	34,9%	528,9
35-40	90,3%	35,1%	603,0
40-50	88,2%	37,3%	673,2
50-60	80,0%	39,7%	663,6
60-120	77,8%	40,4%	513,1
Education[4]			
Early Childhood	79,9%	35,8%	541,3
Elementary	82,9%	34,9%	504,2
High-School	85,9%	35,3%	488,9
Complete College	86,3%	33,8%	412,7

[1] Total number of individuals working on the delivery platform found in the 2018 RAIS database.
[2] The racial/skin color categories are the same as those used by the Annual Social Information Report (RAIS).
[3] The age shown is the average age of the individuals.
[4] The education level considered is the completed education level.

After the explanatory variables selection, equation (2) was estimated once again, and beyond all previously observed factors used, it was included the explanatory variables "Delivery by Motorbike", "Lunchtime Deliveries", "Deliveries mean', being the last one used with logarithmic transformation.

The regression results exposed on Table 4 show important resolution after including the selected variables. Column (1) repeat results previously exposed, without the new variables inclusion. As for column (2), the regression results including the use of motorbikes as control, that is, beyond other factors, the regression was controlled by earnings differentials of individuals that used motorcycle to complete their orders. In this setting, it was observed that despite the relative small result magnitude, pay differential between men and women cease to exist. As for individuals using motorbikes, the hourly wages are 8.43% larger compared to observations that used other means of transportation. On the racial perspective, salary differential remains negative, but is no longer significant.

Column (3) exposes outcomes of the regression controlled by the "Lunchtime Deliveries" explanatory variable. It was verified that with this control, the earnings differential between men and women exists once again, with women having 1.87% less than men. Individuals that completed their orders at this period got 21.40% more pay compared to observations that made deliveries at other times of the day. Salary differential on race still is negative.

Regression results controlled by the quantity of deliveries are exposed at column (4). In this situation, not only earnings differential between men and women is suppressed, but women now have 1.56% higher hourly wages than men. In regards to race, the salary differential is still negative and not significant

Results when controlling the equation with all selected explanatory variables are shown on column (5). In this situation, gender earnings differential inverts, with women receiving 2.08% more than men. Such result support the hypothesis that at the gig economy there is a tendency to reduce wage disparity through a "neutral" payment method, in other words, that the discrimination opportunities and work segregation are removed. However, even though it is not an expressive pay differential, it is extremely important. It indicates that the market is moving towards a change, although in small steps. In regards to race, however, results do not strengthen the gig economy neutrality hypothesis. Black workers remain with smaller earnings when compared to white labourers, but the result is not statistically significant.

It is important to highlight that, in all models, race differential holds, but it is not possible to affirm with conviction that such coefficient is statistically different from zero. We can also observe that when we control for the three variables in column (5), older individuals start to earn less, indicating a decline in wages with age. Beyond that, when focusing the analysis on delivery platform workers that have a college degree, it can be noticed that the pay differential remains even when controlling by the explanatory variables. This situation is a contrast with Human Capital Theory, that arguments a higher education leads to a increase on earnings.

Table 4: Wage Determinants in the Delivery Platform 2019/2020

Variable	Wage Differential				
	Delivery Platform				
	(1)	(2)	(3)	(4)	(5)
Women	-0.0143*	0.0042	-0.0187**	0.0156**	0.0208***
	(0.0058)	(0.0038)	(0.0059)	(0.0057)	(0.0035)
Physical Disability	0.0005	0.0062	0.0022	0.0061	0.0104
	(0.0106)	(0.0107)	(0.0104)	(0.0096)	(0.0090)
Motorcycle		0.0843***			0.0464*
		(0.0243)			(0.0224)
Lunchtime Deliveries			0.2140***		0.1830***
			(0.0212)		(0.0180)
Log No. of Deliveries				0.0800***	0.0769***
				(0.0013)	(0.0013)
Race[1]					
Black	-0.0037*	-0.0019	-0.0044**	-0.0026	-0.0023
	(0.0016)	(0.0017)	(0.0016)	(0.0016)	(0.0017)
Age[2]					
16-18	-0.0173	-0.0059	-0.0171	0.0030	0.0087
	(0.0092)	(0.0075)	(0.0088)	(0.0080)	(0.0063)
18-20	-0.0064*	-0.0046	-0.0063*	0.0046	0.0053
	(0.0032)	(0.0030)	(0.0031)	(0.0029)	(0.0027)
25-30	0.0005	-0.0008	0.0006	-0.0103***	-0.0105***
	(0.0024)	(0.0024)	(0.0022)	(0.0022)	(0.0021)
30-35	0.0045	0.0025	0.0042	-0.0143***	-0.0149***
	(0.0024)	(0.0027)	(0.0026)	(0.0022)	(0.0024)
35-40	-0.0051	-0.0059	-0.0050	-0.0299***	-0.0293***
	(0.0038)	(0.0041)	(0.0035)	(0.0032)	(0.0032)
40-50	-0.0044	-0.0028	-0.0081*	-0.0364***	-0.0374***
	(0.0037)	(0.0038)	(0.0034)	(0.0032)	(0.0029)
50-60	-0.0200*	-0.0140	-0.0286**	-0.0445***	-0.0476***
	(0.0087)	(0.0089)	(0.0089)	(0.0089)	(0.0088)
60-120	0.0530	0.0622	0.0443	0.0217	0.0206
	(0.0509)	(0.0520)	(0.0524)	(0.0440)	(0.0454)
Education[3]					
Complete Early Childhood	0.0142*	0.0164**	0.0142*	0.0151**	0.0162**
	(0.0057)	(0.0056)	(0.0056)	(0.0052)	(0.0051)
Complete Elementary	0.0036	0.0055	0.0045	0.0034	0.0052*
	(0.0032)	(0.0029)	(0.0029)	(0.0028)	(0.0025)
Complete College	-0.0129***	-0.0138***	-0.0110***	-0.0042	-0.0034
	(0.0033)	(0.0033)	(0.0032)	(0.0032)	(0.0032)
Fixed Effects					
Municipality	yes	yes	yes	yes	yes
Sector (2018)	yes	yes	yes	yes	yes
Occupation (2018)	yes	yes	yes	yes	yes
Observations	133.856	133.856	133.856	133.856	133.856
R^2	0.12872	0.13665	0.14741	0.24887	0.26461

Reference groups: 1 White men; 2 Age between 21-24 years old; 3 Complete High School; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

6. Conclusion

This present study examined the impact of the gig economy on gender and racial wage differentials, through use of data from one of the most relevant companies of the delivery applications branch. By using a simple linear regression method for a Mincer equation of pay determination, this work compared earnings differentials for the same group of workers, analyzing them both in the gig economy and in the formal traditional labour market.

It was observed that, in the formal market, when controlling by all observable factors, women from the sample earned, by hours worked, 5.83% less than men. In the delivery platform, under the same circumstances, the differential remained but was reduced to 1.43%. From a racial perspective, both in the formal market and on the delivery platform, Black workers earn less than white workers, although this differential is smaller than in the case of gender. However, by knowing that, in theory, the platform is developed so that discrimination and segregation opportunities are eliminated, this work investigated more markedly possible reasons for remaining gender and racial payment differentials by deliveries.

By selecting 3 explanatory variables, this present study discovered that, when moderating the workers hourly-wage equation with such variables, the gender earnings differential no longer exists and women receive 2.08% more than men. This result supports that the neutral payment system is in fact neutral in regards to characteristics usually subject to discrimination in the labour market. However, it is not an expressive differential, but it is important because it confirms that, from a gender perspective, the market is moving towards a change. The same result does not occur in regards to race. Although the results magnitude is relatively small, black workers still earn less than white labourers on the delivery platform. The true reason for this discrepancy and its persistence has not yet been fully uncovered, but it can be investigated in future studies.

It was previously believed that algorithm-based commerce could reduce the effects of gender and racial wage discrimination, as the role of humans is minimized in this type of transaction. Instead, Fisman and Luca (2016) say that trust on algorithms, in many cases, can lead to, instead of suppress, discrimination. With the analysis conducted, this present study observed a significant reduction in gender wage differentials on the delivery platform. The same cannot be observed regarding racial differentials, primarily due to the lack of statistical significance in the analysis. However, something that could be done by platforms to diminish such discrimination, is to have a larger knowledge of the gender and racial compositions of its employees and do adjustments accordingly to eradicate wage - and non wage - discrepancies. It is clear the potential of the Internet and the gig economy to create markets free from considerations of race, gender, and age. Now, with all the evolution and knowledge, it is expected that platforms will use their power to create a more inclusive economy with fewer gender and racial wage disparities.

Appendix A. Alternative Mincerian Specification

In the main analyses, wage differentials among workers were examined in two situations. The first involved regression equations comparing the compensation of workers in the formal labor market and delivery platform workers, each estimated using two different models concerning the inclusion of fixed effects. The second situation investigated the possible reasons for the remaining differentials identified in the first situation.

In this section, a robustness test is conducted, where equations (1) and (2) were re-estimated, considering the interaction of gender and race variables along with the other variables previously used. This test was performed to determine if there are any differences in the results previously obtained when including the interaction of these variables. It is important to note that the variable 'White Man' was used as the reference group for the comparisons.

Table 5 focuses on comparing compensation between workers in the formal labor market and delivery platform workers. It is observed that, in general, in columns (1) and (3), where there is no control for the sector and occupation of the job observed in 2018, when we centralize the analysis solely on women, both white and black women continue to earn less than white men. However, it is worth noting that the number of observations in this category is only 4.9% of the total number of women, who make up only 5.1% of the total sample. When the analysis is focused solely on the male gender, it is observed that black men earn less than white men, both in the formal labor market and on the delivery platform.

In columns (2) and (4), where controls for sector and occupation of the job observed in 2018 are included, when we narrow the analysis solely to women in the formal labor market, they continue to earn less than men. However, in the formal labor market, the coefficient for black women becomes positive, which is contrary to what is expected according to the literature. On the delivery platform, in column (4), it is stated that the wage differential reverses, but only for black women. When focusing the study solely on men, it is noted that, both in the formal labor market and on the delivery platform, black men continue to earn less than white men.

Table A.5: Interaction between Gender and Race, Wage Determinants in RAIS 2018 and at the Delivery Platform 2019-2020

	Wage Differential			
	Formal Market (RAIS)		Delivery Platform	
Variable	(1)	(2)	(3)	(4)
White Woman[1]	-0.0819***	-0.0606***	-0.0186*	-0.0128*
	(0.0051)	(0.0047)	(0.0085)	(0.0073)
Black Woman	-0.0960***	0.0629***	-0.0282***	-0.0196*
	(0.0086)	(0.0061)	(0.0083)	(0.0080)
Black Man	-0.0086**	-0.0027	-0.0041*	-0.0035*
	(0.0027)	(0.0020)	(0.0017)	(0.0016)
Age[2]				
16-18	-0.2200***	-0.1799***	-0.0203	-0.0173
	(0.0080)	(0.0061)	(0.0109)	(0.0093)
18-20	-0.1097***	-0.0832***	-0.0093*	-0.0064*
	(0.0036)	(0.0030)	(0.0040)	(0.0032)
25-30	0.1133***	0.0807***	0.0028	0.0005
	(0.0053)	(0.0042)	(0.0034)	(0.0024)
30-35	0.1843***	0.1282***	0.0088**	0.0045
	(0.0072)	(0.0063)	(0.0027)	(0.0024)
35-40	0.2133***	0.1497***	0.0024	-0.0051
	(0.0107)	(0.0067)	(0.0052)	(0.0038)
40-50	0.2384***	0.1670***	0.0016	-0.0044
	(0.0118)	(0.0069)	(0.0049)	(0.0037)
50-60	0.2621***	0.1947***	-0.0171	-0.0200*
	(0.0184)	(0.0141)	(0.0090)	(0.0087)
60-120	0.2275***	0.1299**	0.0553	0.0529
	(0.0468)	(0.0438)	(0.0448)	(0.0509)
Education[3]				
Complete Early Childhood	-0.0158	-0.0054	0.0156**	0.0142*
	(0.0154)	(0.0112)	(0.0057)	(0.0057)
Complete Elementary	-0.0118	-0.0215**	0.0032	0.0036
	(0.0076)	(0.0072)	(0.0036)	(0.0032)
Complete College	0.2103***	0.1154***	-0.0170***	-0.0129***
	(0.0095)	(0.0058)	(0.0025)	(0.0033)
Fixed Effects				
Municipality	yes	yes	yes	yes
Sector (2018)	no	yes	no	yes
Occupation (2018)	no	yes	no	yes
Observations	133.856	133.856	133.856	133.856
R^2	0.216	0.387	0.116	0.128

Reference groups: 1 White men; 2 Age between 21-24 years old; 3 Complete High School; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6 exposes regression results after including explanatory variables previously selected and the interaction of gender and race variables. Column (1) repeats formerly shown results, not including new variables, where all race/ethnicity categories of men and women earn less than white men. Column (2) shows regression results, including motorbike usage as control. In this situation, even though results have a small magnitude, earning differentials cease to exist in all race/ethnicity categories for women. As for male individuals, black men continue to earn less than white men.

Column (3) exposes regression outcomes controlled by lunchtime deliveries explanatory variable. With this control, it is verified that wage differentials reappears in all race/ethnicity categories for both women and men. Regression results controlled by the explanatory variable number of deliveries are present in column (4). In this situation, the same result as the one found in column (2) repeats, where despite being of a small magnitude, earnings differential no longer exists in all race/ethnicity categories for women, but still exists for black men.

When controlling the equation by all above cited explanatory variables, the results are shown in column (5). In this scenario, gender pay differential inverts, with white and black women earning, respectively, 1.89% and 1.92% more than white men. These results continue to support the hypothesis that the gig economy tends to reduce gender wage disparities through 'neutral' payment systems. However, the same result is not identified among men, with blacj men still earning less than white men.

Thus, it can be concluded that even with the interaction between gender and race, there are no significant changes in the previously obtained results. It is important to highlight that, due to this combined classification of gender and race variables and the reduced precision of the coefficients, the inference of results in the models was limited.

Table A.6: Interaction between Gender and Race, Wage Determinants in the Delivery Platform 2019-2020

	Wage Differential				
	Delivery Platform				
Variable	(1)	(2)	(3)	(4)	(5)
White Woman[1]	-0.0128*	0.0037	-0.0178*	0.0152*	0.0189***
	(0.0073)	(0.0050)	(0.0076)	(0.0068)	(0.0048)
Black Woman	-0.0196*	0.0038	-0.0243**	0.0115	0.0192**
	(0.0080)	(0.0076)	(0.0080)	(0.0073)	(0.0065)
Black Man	-0.0035*	-0.0020	-0.0043**	-0.0025	-0.0024
	(0.0016)	(0.0016)	(0.0016)	(0.0015)	(0.0016)
Motorcycle		0.0844***			0.0464*
		(0.0244)			(0.0224)
Lunchtime Deliveries			0.2140***		0.1830***
			(0.0212)		(0.0180)
Log No. of Deliveries				0.0800***	0.0769***
				(0.0013)	(0.0013)
Age[2]					
16-18	-0.0173	-0.0059	-0.0171	0.0030	0.0087
	(0.0093)	(0.0075)	(0.0088)	(0.0080)	(0.0063)
18-20	-0.0064*	-0.0046	-0.0063*	0.0046	0.0053
	(0.0032)	(0.0030)	(0.0031)	(0.0029)	(0.0027)
25-30	0.0005	-0.0008	0.0006	-0.0103***	-0.0105***
	(0.0024)	(0.0024)	(0.0022)	(0.0022)	(0.0021)
30-35	0.0045	0.0025	0.0042	-0.0143***	-0.0149***
	(0.0024)	(0.0027)	(0.0026)	(0.0022)	(0.0024)
35-40	-0.0051	-0.0059	-0.0050	-0.0298***	-0.0292***
	(0.0038)	(0.0041)	(0.0035)	(0.0032)	(0.0032)
40-50	-0.0044	-0.0028	-0.0081*	-0.0364***	-0.0374***
	(0.0037)	(0.0038)	(0.0034)	(0.0032)	(0.0029)
50-60	-0.0200*	-0.0140	-0.0286**	-0.0445***	-0.0476***
	(0.0087)	(0.0089)	(0.0088)	(0.0089)	(0.0088)
60-120	0.0529	0.0622	0.0443	0.0218	0.0207
	(0.0509)	(0.0520)	(0.0524)	(0.0440)	(0.0453)
Education[3]					
Complete Early Childhood	0.0142*	0.0164**	0.0142*	0.0151**	0.0162**
	(0.0057)	(0.0056)	(0.0056)	(0.0052)	(0.0051)
Complete Elementary	0.0036	0.0055	0.0045	0.0034	0.0052*
	(0.0032)	(0.0029)	(0.0029)	(0.0028)	(0.0025)
Complete College	-0.0129***	-0.0138***	-0.0110***	-0.0042	-0.0034
	(0.0033)	(0.0033)	(0.0032)	(0.0032)	(0.0032)
Fixed Effects					
Municipality	yes	yes	yes	yes	yes
Sector (2018)	yes	yes	yes	yes	yes
Occupation (2018)	yes	yes	yes	yes	yes
Observations	133.856	133.856	133.856	133.856	133.856
R^2	0.129	0.137	0.147	0.249	0.265

Reference groups: 1 White men; 2 Age between 21-24 years old; 3 Complete High School; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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